## Diabetes Analysis Prediction.

importing necessary library

In [200... import numpy as np import pandas as pd import matplotlib.pyplot as plt import seaborn as sns df = pd.read\_csv("diabetes.csv") In [201... df In [202... Glucose BloodPressure SkinThickness Insulin BMI DiabetesPedigreeFunction Age Out[202]: **Pregnancies** Outco 33.6 0.627 26.6 0.351 0.672 23.3 28.1 0.167 2.288 168 43.1 32.9 0.171 36.8 0.340 0.245 112 26.2 0.349 0 30.1 0 30.4 0.315 

768 rows × 9 columns

Data details: 1) Pregnancies: NUmber of times pergnant 2) Glucose: Refers to the blood sugar level measure 3) BloodPressure: Diastolic blood pressure(mm Hg) 4) SKinthinkness: Triceps skin fold thickness(mm) 5) Insulin: serum insulin (mu U/ml) 6) BMI: Body mass index(weight in kg/Height in m ^2) 7) Diabetespedigreefunction:unction which scores likelihood of diabetes based on family history 8) Age: In years 9) Outcomes: Class variable (0-non-diabetic,1-diabetic)

```
In [203... df.shape
Out[203]: (768, 9)
In [204... df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
     Column
                                Non-Null Count Dtype
 0
     Pregnancies
                                                 int64
                                768 non-null
 1
     Glucose
                                768 non-null
                                                 int64
     BloodPressure
 2
                                768 non-null
                                                 int64
     SkinThickness
 3
                                768 non-null
                                                 int64
 4
     Insulin
                                768 non-null
                                                 int64
 5
     BMI
                                768 non-null
                                                 float64
 6
     DiabetesPedigreeFunction
                                768 non-null
                                                 float64
 7
                                768 non-null
                                                 int64
     Age
     Outcome
                                768 non-null
                                                 int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

## Checking Null Values.

```
In [205...
            df.isnull().sum()
                                                0
            Pregnancies
Out[205]:
                                                0
            Glucose
            BloodPressure
                                                0
            SkinThickness
                                                0
            Insulin
                                                0
            BMI
                                                0
            DiabetesPedigreeFunction
                                                0
                                                0
            Age
            Outcome
                                                0
            dtype: int64
            df.describe()
In [206...
                                    Glucose
                                             BloodPressure SkinThickness
                                                                                Insulin
                                                                                               BMI
                                                                                                    DiabetesPedigreeFunct
Out[206]:
                    Pregnancies
             count
                     768.000000
                                 768.000000
                                                 768.000000
                                                                768.000000
                                                                            768.000000
                                                                                        768.000000
                                                                                                                   768.0000
                       3.845052
                                 120.894531
                                                                 20.536458
                                                                             79.799479
                                                                                                                     0.4718
             mean
                                                  69.105469
                                                                                          31.992578
                                  31.972618
                                                  19.355807
                                                                 15.952218 115.244002
                                                                                          7.884160
                                                                                                                     0.3313
               std
                       3.369578
                       0.000000
                                   0.000000
                                                   0.000000
                                                                  0.000000
                                                                               0.000000
                                                                                           0.000000
                                                                                                                     0.0780
               min
              25%
                                                                                                                     0.2437
                       1.000000
                                  99.000000
                                                  62.000000
                                                                  0.000000
                                                                              0.000000
                                                                                          27.300000
              50%
                       3.000000
                                 117.000000
                                                  72.000000
                                                                  23.000000
                                                                             30.500000
                                                                                          32.000000
                                                                                                                     0.3725
              75%
                       6.000000
                                 140.250000
                                                  80.000000
                                                                  32.000000
                                                                            127.250000
                                                                                          36.600000
                                                                                                                     0.6262
                      17.000000 199.000000
                                                 122.000000
                                                                  99.000000
                                                                            846.000000
                                                                                          67.100000
                                                                                                                     2.4200
              max
In [207...
            #df=df.iloc[1:10,]
```

## Visualization.

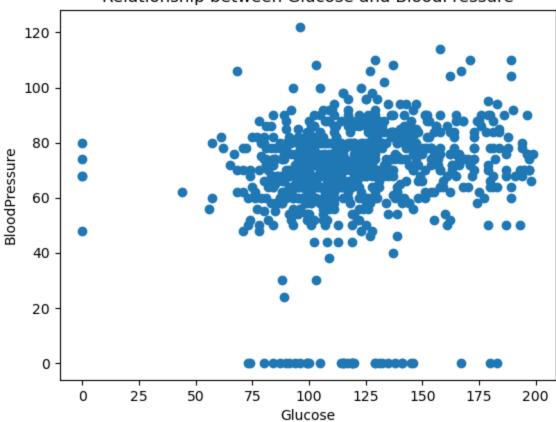
```
In [208... plt.scatter(df['Glucose'],df['BloodPressure'])
    plt.xlabel("Glucose")
    plt.ylabel("BloodPressure")
    plt.title("Relationship between Glucose and BloodPressure")

Out[208]: Text(0.5, 1.0, 'Relationship between Glucose and BloodPressure')
```

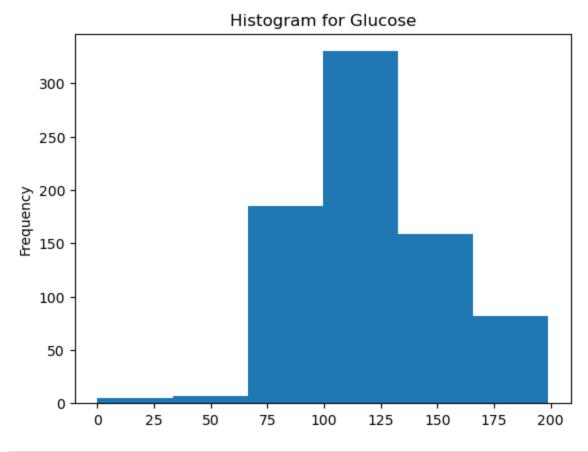
Out[208]: Text(0.5, 1.0, Relationship between Glucose and Bit

Loading [MathJax]/extensions/Safe.js

### Relationship between Glucose and BloodPressure

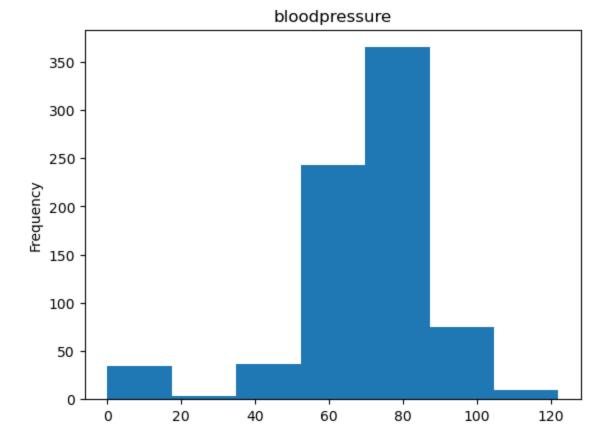


```
In [209... df['Glucose'].plot(kind='hist', bins=6)
   plt.title("Histogram for "+df['Glucose'].name)
   plt.show()
```

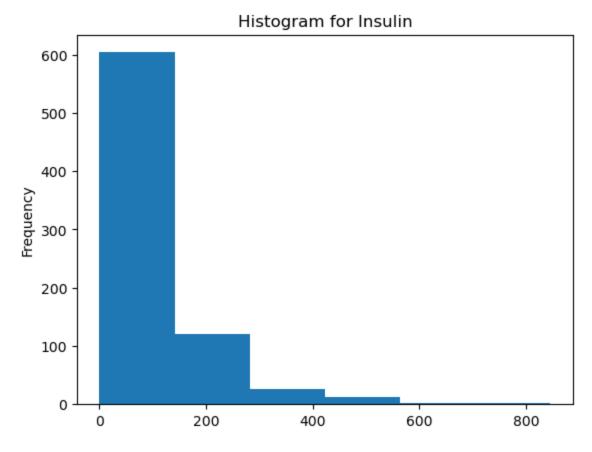


```
In [210... df['BloodPressure'].plot(kind='hist',bins=7)
plt.title("bloodpressure")
plt.show()

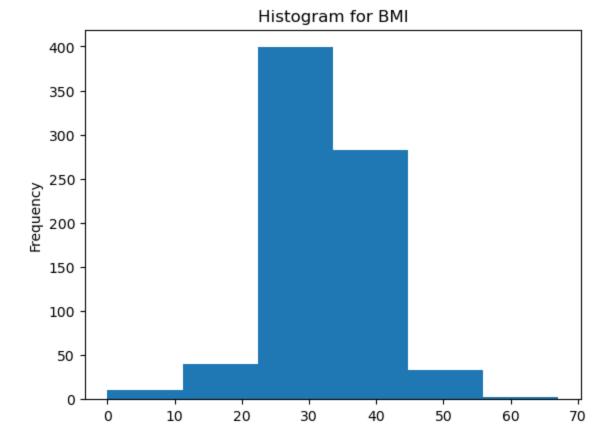
Loading [MathJax]/extensions/Safe.js
```



```
In [211... df['Insulin'].plot(kind='hist',bins=6)
    plt.title("Histogram for "+df['Insulin'].name)
    plt.show()
```



```
In [212... df['BMI'].plot(kind='hist',bins=6)
  plt.title("Histogram for "+df['BMI'].name)
  plt.show()
```



```
In [213... #df = df.iloc[1:1000]
```

In [214... sns.distplot(df['Glucose'])

C:\Users\NANDHINI\AppData\Local\Temp\ipykernel\_5912\2512680699.py:1: UserWarning:

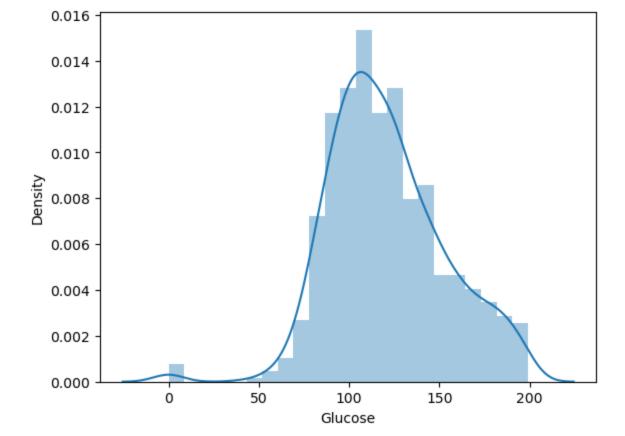
`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

sns.distplot(df['Glucose'])

Out[214]: <Axes: xlabel='Glucose', ylabel='Density'>

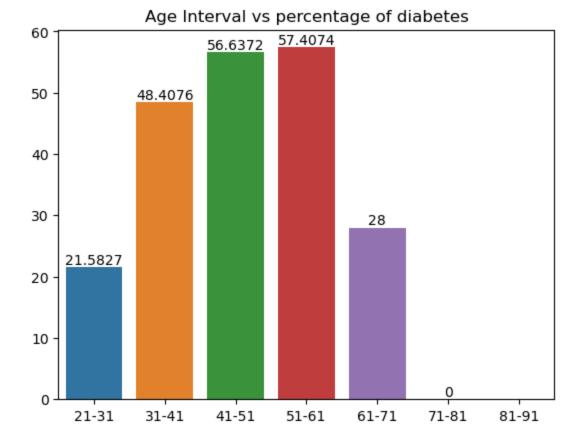


```
In [215... s=df.groupby('Age')['Outcome'].sum()
    s1=df['Age'].value_counts().sort_index()
    d={f'{i+21}-{i+31}':(s[i:i+10].sum()/s1[i:i+10].sum()) for i in range(0,61,10)}

C:\Users\NANDHINI\AppData\Local\Temp\ipykernel_5912\2881464474.py:3: RuntimeWarning: inv alid value encountered in scalar divide
    d={f'{i+21}-{i+31}':(s[i:i+10].sum()/s1[i:i+10].sum()) for i in range(0,61,10)}

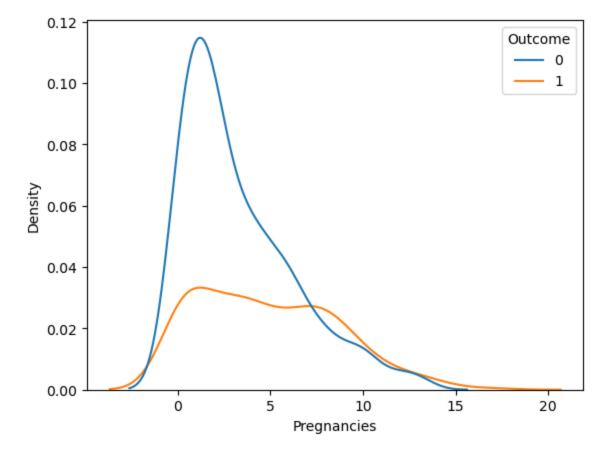
In [216... s=pd.Series(d)
    ax=sns.barplot(x=s.index,y=s.values*100)
    for i in ax.containers:
        ax.bar_label(i,)
    plt.title('Age Interval vs percentage of diabetes')

Out[216]: Text(0.5, 1.0, 'Age Interval vs percentage of diabetes')
```

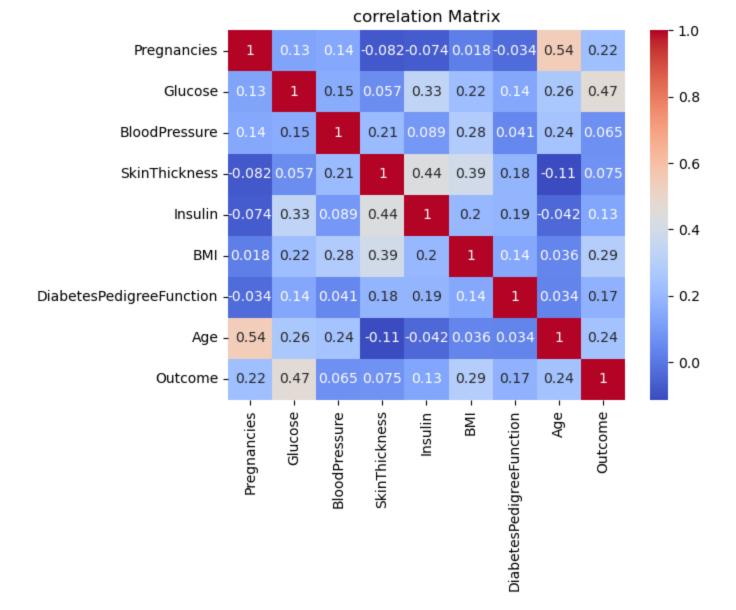


In [217... sns.kdeplot(x='Pregnancies', hue='Outcome', data=df)

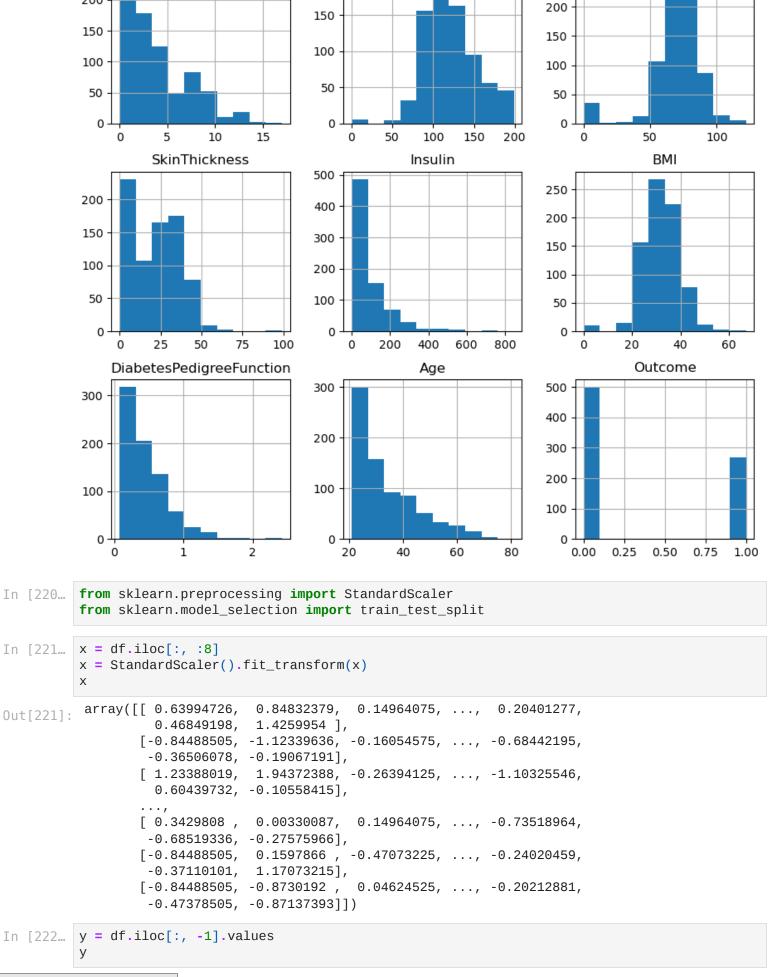
Out[217]: <Axes: xlabel='Pregnancies', ylabel='Density'>



```
In [218... sns.heatmap(df.corr(), annot=True , cmap = 'coolwarm')
   plt.title('correlation Matrix')
   plt.show()
```



In [219... #creating histograms after replacing the zeros
 df.hist(figsize=(10,9))
 plt.show()



Glucose

200

BloodPressure

250

Pregnancies

250

200

```
Out[222]:
                 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1,
                 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0,
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                                                                  0, 1, 0, 0, 1,
                                   1, 0, 0,
                                                         0, 0,
                                                               Θ,
                 1, 0, 0, 0, 1, 0,
                                            Θ,
                                               0, 0, 1,
                                                                  0, 0,
                                                                         1,
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                    0, 0, 0, 0,
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                                   0, 1,
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                 0, 1, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1,
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                 0, 1, 0,
                          0, 0,
                                 0, 1, 1,
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                 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0,
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                                          0, 1,
                                                0, 0, 0,
                                                         0, 1,
                                                               Θ,
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                                                                  0, 1, 0, 0, 0, 0,
                 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0,
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                                                                  0, 0, 0, 1,
                 0, 0, 0, 0, 0, 1,
                                   0, 1, 1, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1,
                 0, 1, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 1, 0, 1,
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                                                               Θ,
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                                             1,
                                                1, 0, 0, 0, 0,
                                                               Θ,
                                                                  0, 1, 0, 0, 0,
                 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1,
                 0, 1, 0, 0, 0, 0, 0, 1,
                                          0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 0,
                 0, 0, 1, 0, 1, 1, 0, 0,
                                          1,
                                            0, 0, 1, 1, 0, 0,
                                                               1,
                                                                  0, 0, 1, 0, 0, 0,
                 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0,
                 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0],
                dtype=int64)
In [223... x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random_state
In [224...
         def perform(y_pred):
              print("Precision : ", precision_score(y_test, y_pred, average = 'micro'))
              print("Recall : ", recall_score(y_test, y_pred, average = 'micro'))
              print("Accuracy : ", accuracy_score(y_test, y_pred))
print("F1 Score : ", f1_score(y_test, y_pred, average = 'micro'))
              cm = confusion_matrix(y_test, y_pred)
              print("\n", cm)
              print("\n")
              print("**"*27 + "\n" + " "* 16 + "Classification Report\n" + "**"*27)
              print(classification_report(y_test, y_pred))
              print("**"*27+"\n")
              cm = ConfusionMatrixDisplay(confusion_matrix = cm, display_labels = ['Non-Diabetic',
              cm.plot()
```

## Gaussian Navie Bayes.

array([1, 0, 1, 0, 1, 0,

1, 0,

1,

1, 0, 1, 0,

1, 1, 1, 1, 1, 0,

```
In [225... from sklearn.naive_bayes import GaussianNB, BernoulliNB
In [226...
          model_gnb = GaussianNB()
          model_gnb.fit(x_train, y_train)
```

```
Out[226]: ▼ GaussianNB
GaussianNB()
```

In [227... y\_pred\_gnb = model\_gnb.predict(x\_test)

In [230... | from sklearn.linear\_model import LogisticRegression, RidgeClassifier

from sklearn.tree import DecisionTreeClassifier, plot\_tree

from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, ExtraTreesClass

from sklearn.neighbors import KNeighborsClassifier

from sklearn.svm import SVC, NuSVC

from sklearn.neural\_network import MLPClassifier

from sklearn.metrics import precision\_score, recall\_score, accuracy\_score, f1\_score, cla

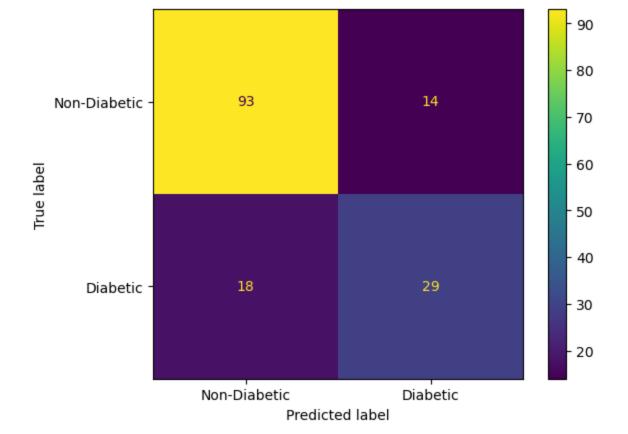
#### In [231... perform(y\_pred\_gnb)

Precision: 0.7922077922077922
Recall: 0.7922077922077922
Accuracy: 0.7922077922077922
F1 Score: 0.7922077922077922

[[93 14] [18 29]]

\*\*\*\*\*\*\*\*\*\*\*\*\*\*

*****	***	Classifica	•		******
	ı	precision	recall	f1-score	support
	0 1	0.84 0.67	0.87 0.62	0.85 0.64	107 47
accurac macro av weighted av	/g	0.76 0.79	0.74 0.79	0.79 0.75 0.79	154 154 154



# Bernoulii Navie Bayes.

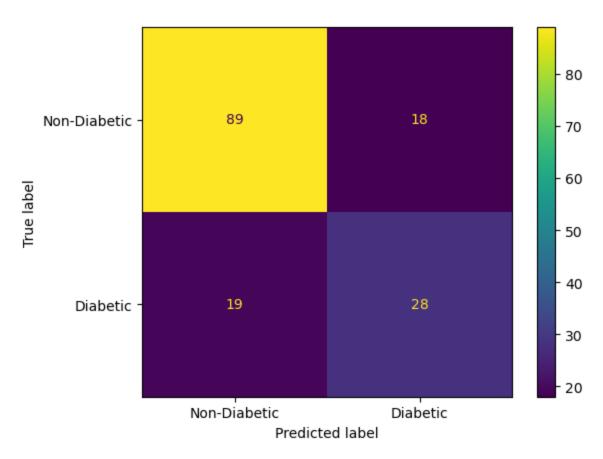
Precision: 0.7597402597402597 Recall: 0.7597402597402597 Accuracy: 0.7597402597402597 F1 Score: 0.7597402597402597

[[89 18] [19 28]]

\*\*\*\*\*\*\*\*\*\*\*\*\*

*****	****	Classific	ation Rep		*****
		precision	recall	f1-score	support
	0 1	0.82 0.61	0.83 0.60	0.83 0.60	107 47
accur macro weighted	avg	0.72 0.76	0.71 0.76	0.76 0.72 0.76	154 154 154

\*\*\*\*\*\*\*\*\*\*\*\*\*



# Logistic Regression

In [237... y\_pred\_lr = model\_lr.predict(x\_test)

Loading [MathJax]/extensions/Safe.js

In [238... perform(y\_pred\_lr)

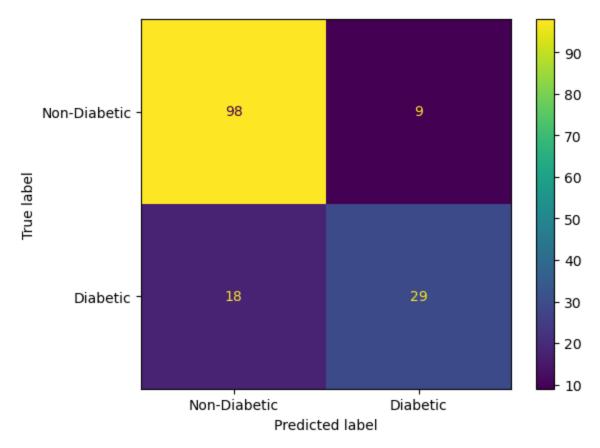
Precision: 0.8246753246753247 Recall: 0.8246753246753247 Accuracy: 0.8246753246753247 F1 Score: 0.8246753246753247

[[98 9] [18 29]]

\*\*\*\*\*\*\*\*\*\*\*\*\*

****	****	Classifica			******
		precision	recall	f1-score	support
	0 1	0.84 0.76	0.92 0.62	0.88 0.68	107 47
accur macro weighted	avg	0.80 0.82	0.77 0.82	0.82 0.78 0.82	154 154 154

\*\*\*\*\*\*\*\*\*\*\*\*\*\*



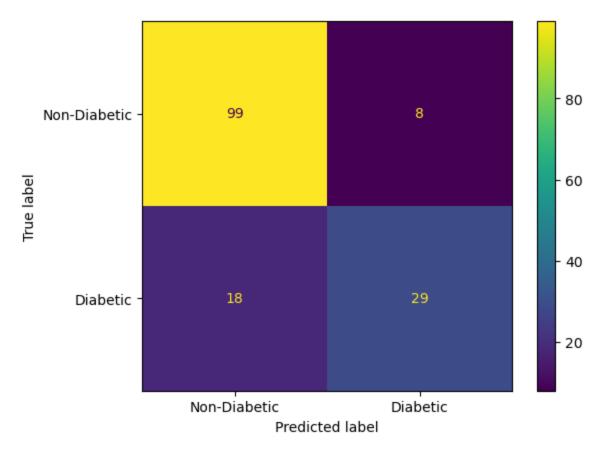
In [242... y\_pred\_rdg = model\_rdg.predict(x\_test)

In [243... perform(y\_pred\_rdg)

Precision: 0.8311688311688312 Recall: 0.8311688311688312 Accuracy: 0.8311688311688312 F1 Score : 0.8311688311688312

[[99 8] [18 29]]

*****	****	Classific	ation Rep		*****
		precision	recall	f1-score	support
	0 1	0.85 0.78	0.93 0.62	0.88 0.69	107 47
accur macro weighted	avg	0.81 0.83	0.77 0.83	0.83 0.79 0.82	154 154 154



```
In [244...
          model_dt = DecisionTreeClassifier()
          model_dt.fit(x_train, y_train)
```

Out[244]: ▼ DecisionTreeClassifier DecisionTreeClassifier()

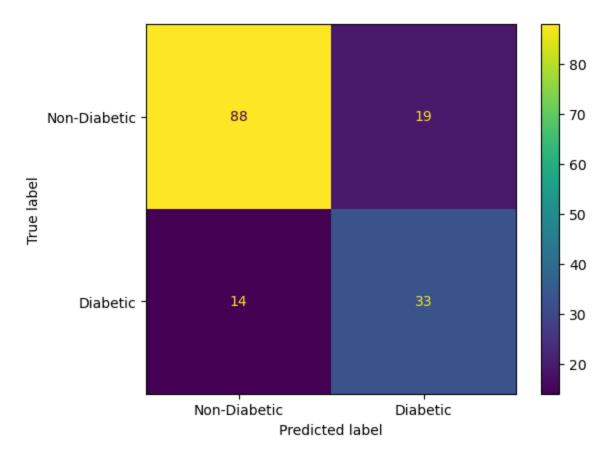
y\_pred\_dt = model\_dt.predict(x\_test) In [245...

In [246... perform(y\_pred\_dt)

Precision: 0.7857142857142857 Recall: 0.7857142857142857 Accuracy: 0.7857142857142857 F1 Score: 0.7857142857142857

[[88 19] [14 33]]

Classification Report					
	I	precision	recall	f1-score	support
	0 1	0.86 0.63	0.82 0.70	0.84 0.67	107 47
accurac macro av weighted av	⁄g	0.75 0.79	0.76 0.79	0.79 0.75 0.79	154 154 154



```
In [247...
         model_rf = RandomForestClassifier()
          model_rf.fit(x_train, y_train)
```

Out[247]: ▼ RandomForestClassifier RandomForestClassifier()

y\_pred\_rf = model\_rf.predict(x\_test) In [248...

In [249... perform(y\_pred\_rf)

Precision : 0.8181818181818182 Recall : 0.81818181818182 Accuracy : 0.81818181818182 F1 Score : 0.81818181818182

[[95 12] [16 31]]

*****	****	Classifica	•		******
		precision	recall	f1-score	support
	0 1	0.86 0.72	0.89 0.66	0.87 0.69	107 47
accur macro weighted	avg	0.79 0.81	0.77 0.82	0.82 0.78 0.82	154 154 154

90 - 80 95 12 Non-Diabetic - 70 - 60 - 50 - 40 16 31 Diabetic -- 30 - 20 Non-Diabetic Diabetic Predicted label

AdaBoostClassifier()

In [251... y\_pred\_ada = model\_ada.predict(x\_test)

### In [252... perform(y\_pred\_ada)

Precision : 0.7792207792207793 Recall : 0.7792207792207793 Accuracy : 0.7792207792207793 F1 Score : 0.7792207792207793

[[89 18] [16 31]]

		**************************************	ation Rep	ort	
		precision	recall	f1-score	support
	0 1	0.85 0.63	0.83 0.66	0.84 0.65	107 47
accur macro weighted	avg	0.74 0.78	0.75 0.78	0.78 0.74 0.78	154 154 154

Non-Diabetic - 89 18 - 70 - 60 - 50 - 40 Non-Diabetic Diabetic Diabetic

Predicted label